Examining Tertiary Education Amid the War in Ukraine: A Synthetic Control Approach

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Abstract

War consistently imposes significant challenges to the functioning and advancement of higher education. To identify the key trends in the development of tertiary education in Ukraine during 2014-2021 amid the war, the synthetic control method (SCM) was employed. The outcome variable for assessing tertiary education development is the gross enrolment ratio of the relevant age group. The broadest set of predictors influencing the dependent variable, for which statistical data is available on the World Bank website, consists of eighteen indicators. Through statistical and expert analysis, sixteen countries were selected for inclusion in the control group. The pre-war period was defined as 2000-2013, with 2014 marking the war's onset, and 2015-2021 representing the war years. In the first stage, a synthetic model is constructed using the broadest possible dataset. In the second stage, the model's sensitivity is analyzed, leading to the reduction of predictors to thirteen and the control group to ten countries. Consequently, the adequate synthetic model for the development of tertiary education in Ukraine from 2014 to 2021 was established. A placebo test confirmed that the observed gap between actual and synthetic values for tertiary education in Ukraine is not coincidental. The SCM analysis revealed that, without the war, a decline in demand in tertiary education would have been predicted for the 2014-2021 period. The observed gap underscores the significant impact of the war on Ukraine's higher education system, providing valuable insights for shaping policy initiatives aimed at advancing tertiary education in the post-war era.

Keywords: Higher education, synthetic control method, treated unit, control units, predictors, forecasting.

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1. Introduction

Higher education is a key driver of economic and social advancement in a country. This is because a well-educated workforce contributes to the generation and implementation of innovations, enhances the competitiveness of the national economy, fosters cultural and intellectual growth, supports the achievement of sustainable development goals, and addresses pressing environmental challenges.

The ongoing war has a multifaceted impact on the development of tertiary education. On the one hand, it results in significant challenges, including the destruction of higher education institutions, reduced access to educational resources, and the forced displacement of academic staff and students. On the other hand, it can serve as a catalyst for innovation in educational technologies, accelerate reforms in tertiary education, enhance knowledge exchange between universities, and stimulate research in areas such as military technologies and the social, economic, and environmental consequences of the war. Given Ukraine's post-war economic recovery initiatives, understanding the nuances of tertiary education development during the war is of particular importance.

The beginning of war in Ukraine in 2014 marked the beginning of disruptions to the integrity of Ukraine's tertiary education system, compelling higher education institutions to adapt to the heightened risks. Despite these challenges, between 2014 and 2021, several government initiatives were launched to bolster the potential of Ukraine's tertiary education sector and enhance its contribution to national economic development. A pivotal milestone was the adoption of the Law of Ukraine "On Higher Education" in December 2014, which aimed to develop competitive human capital and address the state's and labour market's demand for qualified professionals (Verkhovna Rada of Ukraine, 2014). This legislation outlines the key directions for modernizing tertiary education, focusing on its integration into the European Higher Education Area, promoting academic, organizational, and financial autonomy, and enhancing the quality of educational services.

Furthermore, reforms in tertiary education have continued with the establishment of the National Agency for Higher Education Quality Assurance (NAHEQA) in 2015 (CMU, 2015). Its primary objectives were to raise the standards of education for higher education students, taking into account the need for integration into the international educational community and fostering the competitiveness of Ukrainian higher education institutions. At the global level, Ukraine has also committed to improving the quality of tertiary education, with a particular focus on sustainable development. In line with Sustainable Development Goal 4, "Quality Education", it is crucial for Ukraine not only to enhance the quality of tertiary education and ensure its strong connection with scientific research, but also to promote the creation of educational and scientific hubs within the country (SSSU, 2025). Efforts to build an effective tertiary education network in Ukraine have continued with the development of the draft "Higher Education Development Strategy for 2021–2031" (Ministry of Education and Science of Ukraine, 2020), which serves as a roadmap for strengthening the country's professional, scientific, and educational potential, based on the principles of continuous professional and personal development.

Consequently, policy initiatives in the field of tertiary education play a pivotal role in developing a national framework for strengthening the capacity of higher education and integrating it into the global and European higher education area. Despite the war, reforms in tertiary education have continued, resulting in the adoption of the "Strategy for the Development of Higher Education in Ukraine for 2022-2032" (CMU, 2022).

From this perspective, a quantitative assessment of the impact of the war on the development of tertiary education in Ukraine between 2014 and 2021 becomes essential in ensuring the sector's resilience during crises and informing policy decisions. The synthetic control method (SCM) is expected to contribute to a better understanding of the challenges, opportunities, and long-term consequences of the war for the tertiary education sector, offering valuable insights for the policy framework designed to support higher education amid the ongoing war. This approach also promises a deeper understanding of future trends related to integration into the European Higher Education Area and Ukraine's post-war recovery.

2. Literature Review

Academic discussions on the value of tertiary education for economic and social improvements, innovation, and addressing urgent environmental issues remain among the central focuses of scholarly attention both in term of consequences for employability of graduates (Jarząbek & Stolarska-Szeląg, 2024; Kołodziej & Kołodziej-Durnaś, 2024; Roshchyk et al., 2024) and country-level outcomes (Hrynkevych et al., 2022; Samoliuk et al., 2024). Based on data 284 European regions (NUTS 2) over an 18-year period (2000-2017), Agasisti and Bertoletti, employing a sys-GMM model, demonstrated that an increase in the number of universities in a region contributed to regional economic growth, with research quality and specialisation in STEM subjects being the key factors positively influencing regional economic development (Agasisti & Bertoletti, 2022). Lilles and Rõigas, exploring the relationship between higher education students and economic growth at the NUTS 2 level in Europe during 1998-2008, found that the growth of knowledge-intensive employment was associated with an increase in GDP per capita and R&D expenditures (Lilles & Rõigas, 2015). Similar findings are confirmed for non-EU countries (Gasimov et al., 2023) and the OECD countries based on links between migration of highly skilled migrants, including students, and economic resilience of a country (Mishchuk et al., 2024). Using a panel least squares model (fixed and random effects) for a sample of thirty-five European countries over the period 1995-2019, Bacovic et al. (2022) concluded that the contribution of tertiary-educated workers to output growth and R&D investment in high-tech manufacturing and knowledge-intensive services was higher than the average for all sectors. Consequently, the development of tertiary education can serve as a driver of economic and social improvements at the regional level through the generation of new knowledge and enhancing human capital.

The position of tertiary education is evidently influenced by various social, economic, and political factors that are country-specific. Using the ARDL methodology with structural decomposition, Coman (Nuţă) et al. (2023) analysed the impact of public spending on education on economic growth in 11 former communist countries of Eastern Europe that later became EU members. By specifying the parameters of multiple pooled regression models for 28 EU countries over the period 2013-2019, Kichurchak (2021) identified the key drivers impacting the higher education market in the EU, with a focus on public and private higher education institutions. Comparing estimates of the lower bound of inequality of opportunity in higher education (EIOp) for 31 European countries and using two waves of the EU-SILC survey, Palmisano et al. (2022) found a negative relationship between EIOp and real GDP per capita. This finding suggests that greater equality of opportunity in higher education and economic growth are complementary goals. Furthermore, it indicates that the development of tertiary education occurs within a complex and dynamic economic and social environment that influences accessibility.

Moreover, higher education is considered a strategic element in advancing the knowledge economy and achieving competitive advantages (Popescu, 2012a,b). By modelling economic growth in Ukraine during 1995-2017 concerning the knowledge intensity, higher education, and knowledge factors, Korolkov and Lytvyn (2020) showed that GDP dynamics in the country have not gained momentum under the influence of these critical factors, unlike in the USA, China, and Israel. Chentukov et al. (2021) after grouping 50 countries and constructing a matrix of relationships between the Univestas 21 index and the Global Competitiveness Index, found that education has a significant impact on global competitiveness: a high impact for countries with an average level of competitiveness, a moderate impact for highly competitive countries, and a weak impact for countries with low competitiveness. Using data from 32 OECD countries and partner countries for 2014-2018 and applying the Ward clustering method, Hryhorash et al. (2022) identified significant correlations between the level of competitiveness of tertiary education and the amount of funding per student across five clusters of countries, including the cluster encompassing Ukraine. Based on the estimation of parameters from multiple pooled regression models for 28 EU countries for 2013-2019 Kichurchak (2022) found the primary social and economic factors influencing budgetary funding for higher education in the EU countries and highlighted necessity of increasing the level of public funding for tertiary education to promote sustainable and human development in Ukraine. Marhasova et al. (2023) argued that tertiary education has a significant positive impact on the dynamics of sustainable development in Ukraine and its regions, while digitalisation has enabled universities to maintain a competitive position in the of educational services market amidst the challenges posed by COVID-19 and military actions. In a nutshell, enhancing the competitiveness of tertiary education is emerging as a priority in public policy across various countries, underscoring its critical role in sustainable development and economic growth.

Initiatives aimed at the development of the tertiary education system are crucial for achieving sustainable development and its core objectives. By assessing the integration of higher education into key policy activities, Owens (2017) identified publicly funded research and regional partnerships as essential for enabling the sector to actively contribute to sustainable development. Žalėnienė and Pereira (2021) demonstrated that higher education plays a pivotal role in implementing the Sustainable Development Goals (SDGs), particularly in achieving Goal 1 (eradicate poverty in all its forms), Goal 3 (ensure healthy lives and promote well-being for all at all ages), Goal 5 (achieve gender equality), Goal 8 (promote decent work and economic growth), Goal 12 (ensure responsible consumption and production), Goal 13 (combat climate change), and Goal 16 (promote peace, justice, and strong institutions). By constructing non-linear regression models with inflection points, Maneejuk and Yamaka (2021) found that secondary education enrolment rates in ASEAN-5 countries positively impact economic growth, while higher education emerges as a key driver of future growth and sustainability. Using data from 179 countries categorized by income levels, development status (including OECD countries and regions), and Solow's growth theory, Sarwar et al. (2021) concluded that prioritizing education in sustainable development policies is essential for fostering long-term economic growth. Consequently, tertiary education significantly contributes to achieving sustainable development goals, advancing social welfare, and improving environmental conditions.

Simultaneously, the war has had an adverse impact on human capital and the advancement of tertiary education. Employing a human capital indicator that combines the quality and quantity of education and skills in the adult population, Égert and de la Maisonneuve (2023) estimated that the loss of long-term aggregate productivity could reach approximately 7%, primarily due to the deterioration of student learning outcomes and the erosion of employee skills. Lugovyi et al. (2023), analysing the key challenges faced by higher education in Ukraine during the war, emphasized the critical role of universities in the country's post-war economic recovery. Given the war and the subsequent economic recovery of Ukraine, researchers identified key areas for rebuilding and further developing human capital, including improving the quality of tertiary education, expanding adult training and retraining programmes, and providing support for individuals with disabilities (Gorodnichenko et al., 2022; Tsybuliak et al., 2024). Based on an analysis and synthesis of secondary data, Zayachuk (2024) highlighted major responses by the Ukrainian tertiary education system to sustain the quality of education at universities and to implement the SDGs despite the ongoing war. Using the Life Stressor Checklist-Revised (LSC-R) and the Organisational Culture Assessment Instrument (OCAI), Anishchenko et al. (2023) demonstrated the significant impact of military operations on social transformations within higher education, driven by changes in organisational needs and heightened psychological stress. Although the war has had devastating consequences for tertiary education, it also serves as a catalyst that could play a pivotal role in Ukraine's post-war recovery, guided by the principles of sustainable development.

Overall, academics have made valuable contributions to emphasising the importance of tertiary education in driving economic, social, and environmental transformation at both national and regional levels. By employing quantitative research methods, they have assessed the role of higher education in fostering economic growth, advancing sustainable development across various countries, and facilitating post-war recovery in Ukraine. However, this research proposes the application of the SCM to explore dependencies and assess interrelationships that illustrate the impact of the war on tertiary education in Ukraine during the period 2014-2021.

The purpose of this research is to explore key patterns in the development of tertiary education in Ukraine during the war, using the synthetic control method.

The following hypotheses guide the research. Firstly, it is hypothesized that trends in higher education development in Ukraine are tied to the gross enrollment ratio in tertiary education, defined as the proportion of the relevant age group enrolled, which may differ significantly with or without war. Secondly, this indicator may fluctuate due to the war's influence on factors such as labour market transformations, changes in the structure of employment and unemployment among youth, state funding of higher education, and the demographic situation. Thirdly, the potential trajectory of tertiary education development in Ukraine, had the war not occurred, can be forecasted based on a group of countries where no military operations were conducted.

3. Research Methods

3.1. Theoretical Basis for Method Selection

Today, several effective methods exist for investigating the impact of various shocks, events, and policies on system development dynamics. One such method is the SCM. The essence of this method lies in constructing a synthetic trajectory that reflects the development of a treated unit in the absence of the analysed shocks and policy events. The next step involves comparing the actual trajectory, which reflects the impact of certain shocks and unexpected events, and the synthetic trajectory, which is devoid of such impact. The synthetic trajectory is constructed based on a control group of units whose behaviour prior to the intervention closely resembles that of the treated unit and which were unaffected by the shock. This control (synthetic) group serves as a basis for comparison with the treated unit, enabling the assessment of the causal effects of the intervention.

Due to the transparency in the selection of weights for the control units, the SCM generates intuitive and representative results, making it highly effective for analysing complex political, economic, and social phenomena. For instance, Abadie et al. (2015) applied the SCM to estimate the impact of German reunification on the economic growth in West Germany. Another using the SCM is the study by Billmeier, and Nannicini (2013), which analysed the impact of economic liberalisation on economic growth across many countries. By comparing the growth dynamics of liberalised countries with a weighted set of similar but not liberalised countries, the authors identified a key pattern: early reforms had a significantly more positive impact on economic growth than those implemented later. Other empirical applications of the SCM include the evaluation of various interventions influencing the dynamics of socio-economic systems, such as political relations (Acemoglu et al., 2016), trade liberalization reforms in Morocco ("PAS") and their effects on economic growth (Bezbiq, and Hefnaoui, 2024), the impact of Covid-19 vaccination on socio-economic indicators in the region (Langat et al., 2023), the long-term economic consequences of natural disasters (Coffman and Noy, 2011), the effects of the Irish National Recovery Programme of 1987 on sustainable economic growth (Uhr et al., 2022), the impact of laws on the right to bear arms (Donohue et al., 2019), the economic consequences of persistent left-populist regimes in Latin America (Absher et al., 2020), the implementation of a marketing strategy for enterprise development (Paslavska and Synitskyi, 2024), among many others.

The SCM is an extension of the Difference-in-Differences (DiD) method (Doudchenko and Imbens, 2017). Both methods aim to estimate impacts, but while DiD requires a control group with similar characteristics, the SCM allows for the construction of a synthetic control group from a weighted set of units. This flexibility is particularly valuable when it is difficult to create a control group with comparable characteristics.

Moreover, the SCM constructs a counterfactual scenario by combining several control units using optimal weights, which are calculated to minimize the difference in characteristics before the intervention. This enhances the transparency of the analysis process and facilitates clear tracking of the contribution of each control unit. Additionally, the SCM accounts for the heterogeneity of the control group by creating a "synthetic" unit that most closely matches the characteristics of the unit prior to the exposure.

The advantage of the SCM over matching methods (MM) lies in its approach to constructing the control unit. While MM involves identifying the most similar control units to assess the impact, the SCM creates an artificial (synthetic) unit that accounts for the contributions of all units in the control group, weighted according to their relevance. Another strength of the SCM is its intuitive graphical representation of the counterfactual scenario, which is particularly valuable in political analysis and economic research, where clear visualization aids in interpreting results. Given this, the SCM serves as an excellent tool for assessing causal effects in scenarios where traditional methods prove less accurate or challenging to apply. For this reason, its key advantages include flexibility in the design of the control group, adaptability to limited datasets, the ability to account for heterogeneity, and the capability to visually present analytical results.

However, despite its strengths, the SCM has certain limitations and disadvantages, such as sensitivity, including sensitivity to underlying assumptions and variations in the selection of control groups (Abadie et al., 2010). A major challenge is associated with the SCM is achieving a high-quality match of the treated unit and the control group (Ferman and Pinto, 2021; Ben-Michael et al., 2021). Inadequate matching can lead to inaccuracies in assessing the intervention effect. To address this issue, various approaches have been proposed in the academic literature, such as employing negative weights (Wang and Zubizarreta, 2020), optimisation techniques (Vanderbei, 1999), nonparametric methods (Cerulli, 2019), constructing prediction intervals (Cattaneo et al., 2021), and using empirical deviation probabilities (Firpo and Possebom, 2018), among others.

Consequently, by combining methodological rigor with the careful selection of variables, our model aims to provide a comprehensive and detailed analysis of the impact of war in Ukraine on the development of tertiary education during the period 2014–2021. It also addresses the methodological challenges typically associated with this type of research. This analysis will enhance understanding of how the armed conflict is reshaping not only the country's physical infrastructure but also its intellectual and educational domains, which form the foundation for sustainable development.

3.2 Conceptual Framework of the Synthetic Control Method

The mathematical essence of the SCM is considered in this study based on the works of Abadie et al. (2010), Abadie, and Gardeazabal (2003), Douchenko and Imbens (2017). The method is generally based on the following two key assumptions:

1. Independence of the impact from prior outcomes. The impact under examination at the time of its implementation is independent of the outcome under investigation in the pre-intervention period (Xu, 2017). This implies that the event under examination (e.g., war in Ukraine) should not have been predicted nor should it have influenced the variable under scrutiny (e.g., tertiary school enrolment, % gross) prior to its occurrence. In other words, there should be no evidence of future effects that could distort the findings of the analysis.

2. No interaction between the treated units (Cao and Dowd, 2019). Treated units should not interact with the exposure in a manner that alters its effect. This implies that potentially interacting units should be excluded from the control group to isolate the impact on the unit under study. Specifically, this assumption posits that an impact on one country should not influence other countries in the control group. For instance, when exploring the impact of the war on tertiary education in Ukraine, countries that have also been affected by hostilities or possess significant ties with Ukraine would not be appropriate candidates for the control group, as their indicators might also be influenced by the conflict, albeit indirectly.

One of the most challenging aspects of the method is the selection of the control group (donor pool). The quality of this selection directly influences the reliability of the results obtained. Both subjective and objective selection criteria are applied in this process. Subjective selection relies on expert judgment, with donor countries being chosen based on their knowledge and experience in the field of study. In contrast, objective selection employs statistical techniques such as cluster analysis, linear regression, or other quantitative tools. It is crucial to strike a balance between the quantity and quality of control units. While a larger donor pool may lead to more precise results, it can also increase the complexity of their interpretation. It is essential that the donor units possess characteristics similar to those of the treated units, not only at baseline but throughout the entire period under analysis.

Let the researcher consider a set of units indexed by i=1, ..., J+1, where J+1 represents the total the number of observation units, with one treated unit and J control units. The study period is defined as t=1, ..., T.

Let the event under investigation occur at period T_0, where $1 \leq T_0 < T$, with T_0, representing the time when the treatment begins, thus marking the commencement of the exposure periods. Let Y_{it}^N denote the value of a certain indicator for the i-th unit in the period t in the absence of interventions (N – no intervention), and Y_{it}^I in the presence of interventions (I – with intervention). We assume that in the period t = 1, ..., T_0, $Y_{it}^N = Y_{it}^I$: prior to the onset of the intervention, these values do not influence the indicators for the observation unit. Additionally, we assume that the analysed variable does not affect the units in the control group.

The effect of the intervention under study is denoted as α_{it}. Since the effect is observed only for the first unit (i=1) after the intervention time $t > T_0$, the objective of the SCM is to estimate $\alpha_{1t} = Y_{1t}^I - Y_{1t}^N$, where Y_{1t}^N can be represented using a factor model:

$$Y_{it}^N = \delta_t + \theta t \cdot Zi + \lambda_t \cdot \mu i + \varepsilon_{it}, \qquad (1)$$

where δ_t is the overall effect affecting all units in period t, Z_i is the vector of observed covariates characterizing the i-th unit (covariates are variables used to select donor units and control for other factors that may influence the studied indicator), θ_t is the vector of coefficients associated with the covariates, reflecting their impact on the indicator at time t, λ_t is the vector of unobserved latent factors that capture unobserved heterogeneity across units, μ_i is the vector of factor loadings for the i-th unit, indicating how strongly the latent factors affect it, and ε_{it} is the random error term accounting for unsystematic deviations.

Model (1) can be rewritten as:

$$\sum_{j=2}^{J+1} w_j Y_{jt}^N = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \varepsilon_{jt}, \qquad (2)$$

where w_j is the j-th value of the weight vector $W=(w_2,\dots,w_{J+1})$, such that for all $\forall j: w_j > 0 \wedge \sum w_j = 1$.

The goal of the SCM is to find the optimal set of weights $w_2,\dots,w_J$for the donor units, such that the linear combination of their values for the indicator in the pre-intervention period best replicates the values of this indicator for the unit under study. Furthermore, the weights are chosen so that the synthetic control best approximates the values of the covariates for the unit under study.

Doudchenko and Imbens (2017), as well as Abadie and Gardeazabal (2003), have demonstrated that if the model errors are small, the difference between the predicted value of the unit for the synthetic control and the actual value of the treated unit in the pre-intervention period will be negligible.

Consequently, the following method for estimating the effect is proposed ($\alpha_{it} = Y_{it}^I - Y_{it}^N$):

$$\acute{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} \acute{w}_j Y_{jt}. \qquad (3)$$

From a computational perspective, the calculation of the required weights is related to the minimization over the weight vector W of the norm, where , where X_1 is the vector of covariate values for the unit under study prior to T_0+1, and $X$is the matrix of covariate values for the control units. Regardless of the choice of a positive-definite matrix V by the researcher, the optimized norm is written as:

$$\|X_1 - X_0 W\|_V = \sqrt{(X_1 - X_0 W)^` V (X_1 - X_0 W)}. \qquad (4)$$

To obtain the final value of V, an external optimization is performed over the parameter V using a discounting coefficient β, which increases the weight of more recent observations. This optimization can be described as:

$$\sum_{t=1}^{T} \beta^{T-t} \left(Y_{1t} - \sum_{j=2}^{J+1} \acute{w}_j(V) Y_{jt}\right)^2 \to min, \qquad (5)$$

where $\acute{w}$ is the vector of minimum weights obtained in the previous stage.

The V parameters indicate the extent to which each factor (indicator) contributes to the reproduction of the dynamics of the studied indicator in the synthetic control. A high value of extent implies that the respective factor has a greater influence on the similarity between the studied and synthetic units. The weights in the vector W reflect the contribution of each donor unit to the construction of the synthetic control. A high value of a weight signifies that the corresponding unit in the control group is more similar to the treated unit and, therefore, has a greater contribution to the creation of the synthetic control.

Assessing the adequacy of the results obtained using the SCM is a crucial stage of the investigation. This step ensures that the conclusions drawn are robust and contributes to eliminating potential sources of inaccuracy. The simplest methods for such an assessment include visual comparisons of the trajectories of the treated unit and the synthetic control units before and after the intervention, as well as the analysis of residuals (the difference between the actual and predicted values, often represented in a gap graph). Statistical criteria, such as mean squared prediction error (MSPE), root mean square error (RMSE) and mean absolute error (MAE), are employed to quantify the quality of the model fit. Structural break tests are used to detect significant shifts in the data trend following the intervention, while the p-value associated with the impact estimate helps assess the statistical significance of the result.

To explore the potential for improving the results, sensitivity analysis methods are employed to test the model specification. This involves examining how the results change when including or excluding different donor objects, using different time periods, weights or models for unobserved effects, and performing similar calculations for other units where it is known that no effect is present.

Placebo tests are commonly employed to assess the statistical significance of the results obtained (Abadie and Gardeazabal, 2003). This method helps determine whether the observed effect of an intervention is statistically significant or if it may be attributed to random fluctuations. The principle of the placebo test involves constructing a synthetic control for each unit in the control group used to build the synthetic control and calculating the difference between the actual and predicted values. Accordingly, this generates a distribution of differences for all control groups. The observed difference for the unit under study is then compared to this distribution. If the observed difference is significantly different from the distribution of differences for the control groups, it can be concluded that the effect of the intervention is statistically significant.

The advantage of placebo tests lies in their non-parametric nature. This implies that they do not rely on any assumptions regarding the distribution of the data. As a result, placebo tests are more robust in detecting deviations from the normal distribution, which are often encountered in real-world data.

4. Synthetic Control of Ukrainian Higher Education

To investigate the changes caused by war in higher education in Ukraine by using a synthetic control approach, we selected nineteen key predictors to construct a comprehensive representation of the socio-economic context and rigorously assess the impact on higher education. The pre-intervention period (2000–2013) served as the basis for constructing the synthetic control, with 2014 designated as the intervention year and 2015–2021 as the post-intervention observation period. These predictors capture the state's capacity to invest in higher education, youth access to education, and labour market dynamics, which are intrinsically linked to the demand for qualified professionals. This selection ensures a holistic analysis, encompassing both short-term and long-term effects on higher education development. Data for this analysis were sourced from the World Bank database (World Bank, n.d.), ensuring data completeness, relevance, and international comparability. Table 1 shows the selected predictors, categorized by their respective domains of influence.

Table 1. Classification of indicators by their impact on higher education

Group	Indicator
Economic Factors	GDP growth, annual, %
	GDP per capita, constant 2015 US$
	GDP per capita growth, annual %
Social Factors	Employment to population ratio, ages 15-24, female, % (modelled ILO estimate)
	Employment to population ratio, ages 15-24, total, % (modelled ILO estimate)
	Unemployment, total, % of total labour force (modelled ILO estimate)
	Unemployment, youth total, % of total labour force ages 15-24 (modelled ILO estimate)
Demographic Factors	Population ages 15-64, % of total population
	Population ages 15-64, total
	Urban population
	Urban population, % of total population
	Urban population growth, annual, %
Institutional Factors	Wage and salaried workers, total, % of total employment (modelled ILO estimate)
	Employers, total, % of total employment (modelled ILO estimate)
	Employment to population ratio, 15+, total, % (modelled ILO estimate)
	Labour force participation rate for ages 15-24, total, % (modelled ILO estimate)
Education-Specific Factors	Government expenditure on education, total, % of GDP
Research and Development	Research and development expenditure, % of GDP
Outcome	School enrolment, tertiary, % gross

Source: developed by the authors based on (World Bank, n.d.)

The dependent variable, Y_{it} is defined as "school enrolment, tertiary, % gross" – the proportion of the population enrolled in higher education institutions relative to the total population within the relevant age group. This indicator serves as a crucial metric for evaluating the accessibility and coverage of higher education, directly reflecting the level of population's participation in tertiary education. Due to its sensitivity to external shocks, such as armed conflicts or economic crises, Y_{it} effectively captures how social, economic, and demographic transformations impact the higher education system.

The significance of this indicator stems from its capacity to assess not only the volume of educational services provided but also broader societal outcomes, including social mobility, human capital development, and national competitiveness. In the context of Ukraine, this indicator enables the analysis of how war has affected young people's access to higher education and how the government has responded with strategies to preserve educational potential. The dynamics of Y_{it} serves as a valuable marker for evaluating the success of educational reforms and the effectiveness of government policies, particularly during periods of crisis.

The selection of suitable donor countries for the synthetic control method is a critical step in the research process. The appropriate selection of donor countries is crucial for ensuring the reliability of the results and enables us to draw sound conclusions regarding the impact of war on higher education in Ukraine. A primary constraint was the completeness of the available data. Additionally, factors such as geographical proximity, economic development, historical and political ties between countries, urbanization levels, and key higher education indicators were considered. Donor countries should not have experienced large-scale shocks, like war, that could significantly affect their higher education systems. Initially, the donor pool included Estonia, Latvia, and Lithuania (sharing similar challenges in transitioning to a market economy); Poland, the Czech Republic, Slovakia, and Bulgaria (exhibiting comparable levels of development as former members of the Eastern Bloc). Based on statistical analyses and the dynamics of the outcome variable, the list of countries in the control group was expanded to include Hungary, Slovenia, Spain, Ireland, Sweden, Norway, Denmark, France, and Italy. A total of sixteen countries were included in the donor pool.

The R package for the SCM, developed by Abadie *et al.* (2011), was utilized to estimate the model parameters. The model constructed using a donor pool of sixteen countries and eighteen predictors, yielded the results presented in Table 2 and Figures 1a, 1b, and 1c.

Table 2. Synthetic control results for sixteen countries of the donor pool using eighteen predictors

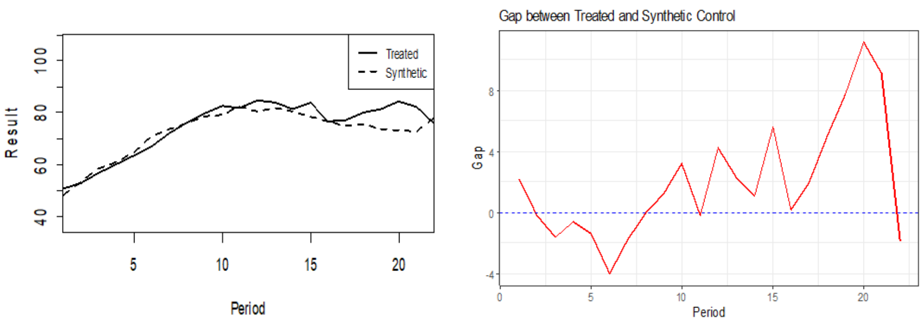
Predictor identifier	Predictor	Solution, v	Donor pool	Solution, w
Factor1	Research and development expenditure, % of GDP	$8.82 \cdot 10^{-05}$	Bulgaria	$2.29 \cdot 10^{-06}$
Factor2	GDP growth, annual, %	$2.14 \cdot 10^{-05}$	**Czechia**	**0.2261**
Factor3	GDP per capita, constant 2015 US$	0.1379	Denmark	0.00043
Factor4	GDP per capita growth, annual, %	$2.37 \cdot 10^{-05}$	Estonia	0.00038
Factor5	Government expenditure on education, total, % of GDP	0.0764	France	0.000154
Factor6	Population ages 15-64, % of total population	0.2956	Hungary	0.000147
Factor7	Population ages 15-64, total	0.0030	Ireland	$1.75 \cdot 10^{-05}$
Factor8	Employment to population ratio, ages 15-24, female, % (modelled ILO estimate)	0.0240	Italy	$9.59 \cdot 10^{-07}$
Factor9	Employment to population ratio, ages 15-24, total, % (modelled ILO estimate)	0.0092	Latvia	$1.78 \cdot 10^{-06}$
Factor10	Unemployment, total, % of total labour force (modelled ILO estimate)	0.0983	Lithuania	$5.10 \cdot 10^{-05}$
Factor11	Unemployment, youth total, % of total labour force ages 15-24 (modelled ILO estimate)	0.2155	Norway	0.0480
Factor12	Urban population	0.0297	Poland	$1.98 \cdot 10^{-05}$
Factor13	Urban population, % of total population	0.0321	Slovak Republic	$0.17 \cdot 10^{-10}$

Predictor identifier	Predictor	Solution, v	Donor pool	Solution, w
Factor14	Urban population growth, annual, %	0.0001	**Slovenia**	**0.5598**
Factor15	Wage and salaried workers, total, % of total employment (modelled ILO estimate)	0.0112	Spain	$4.55 \cdot 10^{-06}$
Factor16	Employers, total, % of total employment (modelled ILO estimate)	0.03825	Sweden	$1.98 \cdot 10^{-05}$
Factor17	Employment to population ratio, 15+, total, % (modelled ILO estimate)	0.0012		
Factor18	Labour force participation rate for ages 15-24, total, % (modelled ILO estimate)	0.0269		

Source: calculated by the authors based on (World Bank, n.d.)

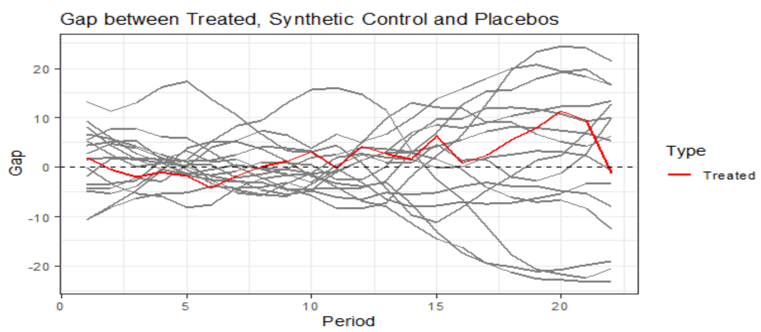
The mean squared prediction errors of the synthetic model, were MSPE(loss v)=5.0623 and MSPE(loss w)=0.0408. The Czech Republic and Slovenia have the greatest influence on the formation of the synthetic trajectory, while Germany, France, Estonia, Hungary, and Norway also have a minor influence.

Figure 1. Results of synthetic control for the control group of 16 countries using 18 predictors (Result – School enrolment, tertiary, % gross; Period – Year: 1 – 2000, 5 – 2004, 10 – 2009, 15 – 2014, 20 – 2019, 22 – 2021)



a) Actual and synthetic trajectories

b) Gap graph



c) Placebo test results

Source: calculated by the authors based on (World Bank, n.d.)

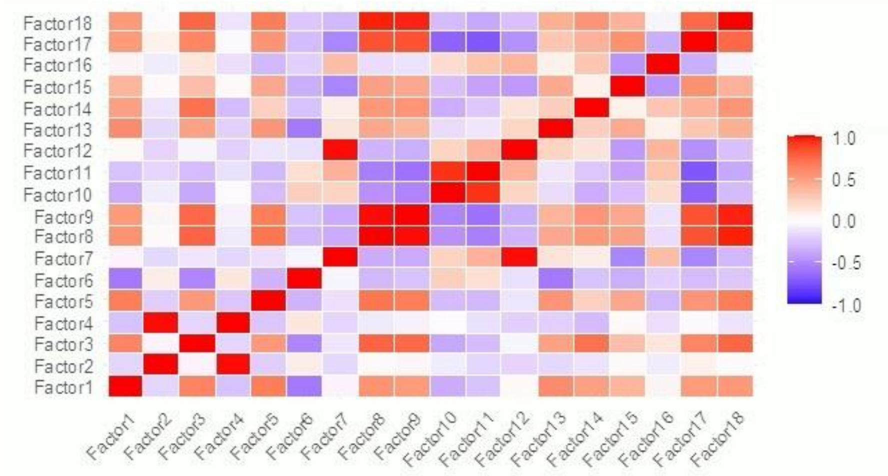
Subsequent steps in implementing the synthetic control method involved assessing the sensitivity of the model to alterations in its specification. Based on these findings, the following steps were identified to improve the model's accuracy:

1. To mitigate the issue of multicollinearity among the predictors, a correlation threshold of |0.9| was applied. A correlation matrix was constructed to visualize the relationships between the predictors (Fig. 2). Pairs of predictors with a correlation coefficient exceeding this threshold were examined, and one predictor from each pair was excluded from the model. The excluded predictors were: Factor 4 – GDP per capita growth, annual, %; Factor 7 – population aged 15-64, total; Factor 9 – employment to population ratio, ages 15-24, total, % (modelled ILO estimate); Factor 10 – unemployment rate, total, % of total labour force (modelled ILO estimate); and Factor 18 – labour force participation rate for ages 15-24, total, % (modelled ILO estimate).

2. Among the donor pool countries, Estonia, Latvia, Hungary, Spain, Norway, and Sweden demonstrated the most significant deviations from the synthetic control during the pre-treatment period. To enhance the model's predictive accuracy, these countries were iteratively removed from the analysis.

3. To ensure comparability across variables with different units of measurement, all variables were standardized. Accordingly, they were displayed in units of standard deviation from the mean.

Figure 2. Correlation matrix heatmap



Source: calculated by the authors based on (World Bank, n.d.)

The sensitivity analysis allowed us to obtain a synthetic model based on a control group of ten countries (Bulgaria, Lithuania, Poland, Czech Republic, Slovakia, Slovenia, Ireland, Denmark, France, Italy) and thirteen predictors for the period from 2000 to 2021. The results of the study are presented in Table 3 and Figures 3a, 3b, and 3c.

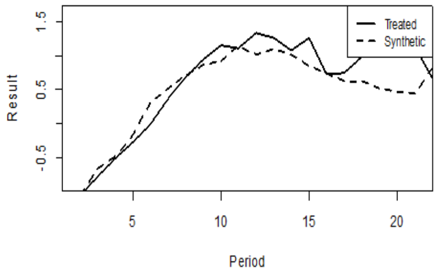
With the given input data, the synthetic control method produced a model with MSPE (loss v)=0.0254 and MSPE (loss w)=0.1136. These relatively low MSPE values suggest that the synthetic model provides a good fit to the observed data. The MSPE for the weights of donor countries is slightly higher and reflects the quality of the selection of weights for donor countries. The limited statistical data and differences in socio-economic indicators of higher education in Ukraine and other countries did not allow us to improve the loss.w characteristic.

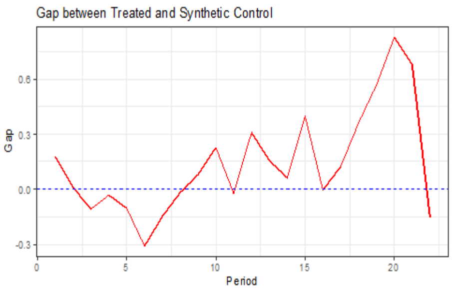
Table 3. Synthetic control results for the ten-country control group using thirteen predictors

Predictor identifier	Predictor	Solution. v	Donor pool	Solution. w
Factor1	Research and development expenditure, % of GDP	$1.59 \cdot 10^{-06}$	Bulgaria	$5.04 \cdot 10^{-05}$
Factor2	GDP growth, annual, %	$3.32 \cdot 10^{-06}$	**Czechia**	**0.2618**
Factor3	GDP per capita, constant 2015 US$	0.0504	Denmark	$9.17 \cdot 10^{-05}$
Factor5	Government expenditure on education, total, % of GDP	0.0503	France	$1.62 \cdot 10^{-06}$
Factor6	**Population ages 15-64, % of total population**	**0.4644**	Ireland	$7.96 \cdot 10^{-08}$
Factor8	**Employment to population ratio, ages 15-24, female, % (modelled ILO estimate)**	**0.0635**	Italy	$1.46 \cdot 10^{-07}$
Factor11	**Unemployment, youth total, % of total labour force ages 15-24 (modelled ILO estimate)**	**0.2857**	Lithuania	0.0003
Factor12	Urban population	0.0003	**Poland**	**0.1012**
Factor13	Urban population, % of total population	0.0188	Slovak Republic	0.0002
Factor14	Urban population growth, annual, %	$8.10 \cdot 10^{-06}$	**Slovenia**	**0.6363**
Factor15	Wage and salaried workers, total, % of total employment (modelled ILO estimate)	0.0500		
Factor16	Employers, total, % of total employment (modelled ILO estimate)	0.0165		
Factor17	Employment to population ratio, 15+, total, % (modelled ILO estimate)	$9.54 \cdot 10^{-05}$		

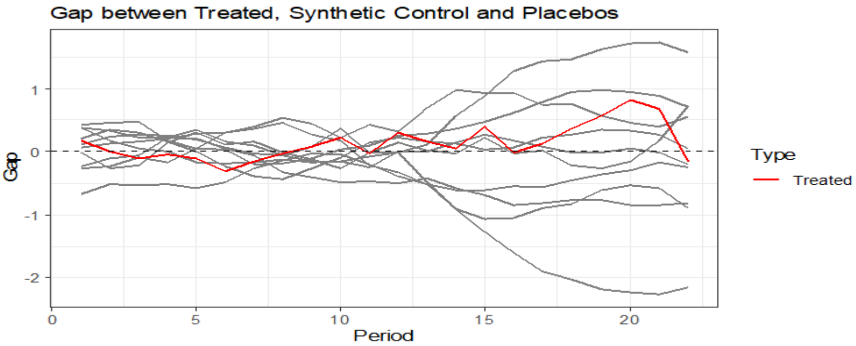
Source: calculated by the authors based on (World Bank, n.d.)

Figure 3. Results of synthetic control for the control group of 10 countries using 13 predictors (Result – School enrolment, tertiary, % gross; Period – Year: 1 – 2000, 5 – 2004, 10 – 2009, 15 – 2014, 20 – 2019, 22 – 2021)





a) Actual and synthetic trajectories b) Gap graph



c) Placebo test results

Source: calculated by the authors based on (World Bank, n.d.)

Table 4 presents the values of the predictors for the treated unit (Ukraine post-2014) and the synthetic control unit, constructed using data from 10 European countries. Notably, the most significant discrepancies between the treated and control units were observed for Factor12 – urban population, Factor13 – urban population, % of total population, Factor16 – employers, total, % of total employment (modelled ILO estimate). These factors were the primary drivers of the differences between Ukraine and the donor pool.

Table 4. Comparison of predictors

Predictor identifier	Treated	Synthetic	Deviation
Factor1	-0.6620	0.1324	-0.7945
Factor2	0.3184	-0.0956	0.4140
Factor3	-1.1969	-0.4512	-0.7458
Factor5	0.4878	-0.0955	0.5833
Factor6	1.3412	1.2622	0.0790
Factor8	-0.1152	-0.2610	0.1458
Factor11	-0.3122	-0.3069	-0.0053
Factor12	1.1848	-0.5395	1.7243
Factor13	-0.2393	-1.2452	1.0059
Factor14	-0.7452	0.1495	-0.8947
Factor15	-0.4256	-0.5736	0.1480
Factor16	-2.0370	-0.3646	-1.6724
Factor17	-0.2844	0.1264	-0.4108

Source: calculated by the authors based on (World Bank, n.d.)

Fig. 2b illustrates the deviation between the actual higher education enrolment rate in Ukraine (the treated unit) and the corresponding value for the synthetic control unit in the pre- and post-intervention periods. Prior to 2014, the gap between the two series is centred around zero, indicating a satisfactory fit of the synthetic control model. Small fluctuations within the range of [-0.3, 0.3] suggest that the synthetic control effectively captured the pre-treatment trends in Ukrainian higher education enrolment, as confirmed by the results presented in Table 5. However, post-2014, a substantial deviation emerged, with the gap widening significantly. The largest gap was observed in 2019, reaching a value of 0.82. Subsequently, in 2021, the gap narrowed and became negative (-0.15). This may be attributed the impact of the COVID-19 pandemic andshort-term policy interventions by the Ukrainian government.

The observed changes in the gap between the actual and synthetic values of the outcome variable can be interpreted as a response of higher education to the deteriorating learning conditions. In particular, according to the survey conducted by Grynyuk *et al*. (2020), about 70% of respondents in Ukraine indicated an imbalance between the necessary conditions that, in their opinion, should be created at universities for the implementation of distance learning and the actual state of affairs in these institutions. The deterioration of higher education in Ukraine in the context of COVID-19 due to the challenges of distance learning can be seen as one of the factors that hinder its development. The situation was similar in 2020-2021 in EU countries. Surveys conducted by Farnell *et al.* (2021) found that students faced difficulties during the COVID-19 pandemic, which include academic progress, well-being, and financial stability. For example, 34.4% of students in EU countries did not often have a quiet place to study (3.3% did not have one at all); 6.4% of students often did not have access to a desk (3.2% did not have access at all); most students have their own computer (89.3%), but almost 60%

reported that they do not always have a stable internet connection; only 31.9% of students reported that they always have access to course materials.

Table 5. Time series comparison of actual and synthetic values for the resultant indicator

Period	Year	Ukraine empirical	Ukraine synthetic	Deviation
1	2000	-1.2398	-1.4155	0.1757
2	2001	-1.0603	-1.0659	0.0056
3	2002	-0.7814	-0.6706	-0.1108
4	2003	-0.5119	-0.4766	-0.0353
5	2004	-0.2740	-0.1686	-0.1055
6	2005	-0.0165	0.2957	-0.3122
7	2006	0.3605	0.5108	-0.1502
8	2007	0.6833	0.7035	-0.0202
9	2008	0.9424	0.8654	0.0770
10	2009	1.1489	0.9218	0.2272
11	2010	1.1049	1.1285	-0.0236
12	2011	1.3206	1.0137	0.3069
13	2012	1.2521	1.0975	0.1546
14	2013	1.0767	1.0172	0.0596
15	2014	1.2449	0.8495	**0.3954**
16	2015	0.7283	0.7362	-0.0079
17	2016	0.7413	0.6157	0.1257
18	2017	0.9772	0.6158	**0.3614**
19	2018	1.0739	0.5073	**0.5667**
20	2019	1.2969	0.4688	**0.8282**
21	2020	1.1216	0.4441	**0.6777**
22	2021	0.6568	0.8105	-0.1537

Source: calculated by the authors based on (World Bank, n.d.)

Figure 2c displays the outcomes of the placebo test. Before the intervention, Ukraine's trajectory closely mirrors those of the placebo groups, thus corroborating the model's validity during the pre-treatment period. Prior to the intervention, Ukraine's trajectory closely mirrored that of its synthetic counterpart and the placebo group trajectories, validating the model's pre-treatment accuracy. However, a significant deviation from the placebo group range emerged post-2014, indicative of a substantial treatment effect. This deviation peaked in 2019, reaching an approximate magnitude of 0.82, considerably exceeding the deviations observed in the placebo groups. Notably, in 2021, a rapid convergence between Ukraine's trajectory and that of its synthetic counterpart became apparent.

The placebo test provides compelling evidence that the observed treatment effect is statistically significant and not attributable to a random chance. The close alignment of Ukraine's trajectory with the placebo group trajectories prior to the intervention supports the adequacy of the synthetic control model in capturing the counterfactual trend. The subsequent significant deviation of Ukraine's trajectory from the synthetic control, particularly in the post-intervention period, strongly suggests that the external shock exerted a substantial impact on higher education outcomes in Ukraine. The absence of such a pronounced deviation in the placebo groups further reinforces the conclusion that the observed effect is specific to Ukraine.

The results of the study confirm the hypothesis of a significant impact of war in Ukraine on the development of higher education. The growing gap between the actual trajectory of Ukraine and its synthetic analogue after 2015 indicates that war has become a significant factor that has significantly affected the accessibility and coverage of education.

In 2014-2021, there were changes in the progress of higher education in Ukraine. Moreover, according to the results of synthetic control, Poland, Slovenia, and the Czech Republic, as countries in the donor pool, were assigned the highest weights. This is due to the fact that these countries and Ukraine share common features while also exhibiting unique characteristics of higher education development, which were formed in view of historical, social and economic conditions. All of these countries are members of the Bologna Process, which ensures the harmonization of educational structures, the creation of conditions for academic mobility of students and teachers, and the use of the European Credit Transfer System (ECTS).

At the same time, there are several notable differences in higher education between Ukraine, Poland, Slovenia and the Czech Republic. According to Kohler *et al*. (2017), the level of autonomy of universities varies: in the Czech Republic, educational institutions have greater decision-making powers, while in Ukraine, reforms which are aimed at decentralizing governance are still ongoing. International integration is another area where differences can be observed. Poland, the Czech Republic and Slovenia, as members of the European Union (EU), have greater access to European educational programmes such as Erasmus+. Ukraine, although not a member of the EU, actively participates in these initiatives, but faces significant obstacles due to current challenges, including the ongoing martial law.

Tuition fees exhibit significant variability. In the Czech Republic, tuition is free for students studying in the Czech language, while in Poland and Slovenia, the cost depends on the chosen programme. In Ukraine, tuition fees vary depending on the speciality and language of instruction, with state-funded programs in place at the state level that covers part of the cost of education.

At the same time, the changes in the gap of the actual and synthetic curves of the gross higher education participation rate demonstrate that the war has increased interest in higher education. This increase may be partially attributed to demographic shifts resulting from the annexation of Crimea and the occupation of parts of Donetsk and Luhansk regions, and the motivation of young men to pursue higher education. Accordingly, the Gender Parity Index (GPI) in higher education in Ukraine until 2014 showed a tendency for women students to predominate at the bachelor's, master's and PhD levels, with an average of 1.13, 1.37 and 1.48, respectively. In 2015-2019, these indicators became lower, with an average of 1.08, 1.27 and 1.05, respectively (SSSU, 2024). During 2014-2021, this trend of change in these indicators may also be due to demographic processes, transformations in the labour market, and the popularisation of STEM fields among women.

The growth of interest in higher education during the war in Ukraine is caused by a number of factors, including its alignment with European standards, increased enrolment of male applicants in higher education, and the need to form highly qualified personnel for the creation of high-tech military products. In the absence of war in Ukraine, the synthetic trajectory of higher education enrolment shows a decline in interest in obtaining higher education in Ukraine. The key reasons for this situation may be the predominance of low-value-added sectors in the Ukrainian economy, which increases the demand for people with blue-collar jobs in the labour market, and a declining perception of the value of higher education in the labour market.

5. Conclusion

Thus, based on the selection of countries, as well as the resulting and predictor indicators, the key features and patterns of tertiary education development in Ukraine are analysed using the

SCM. The empirical and synthetic curves derived demonstrate distinct responses in the dynamics of tertiary education development in Ukraine during the period from 2014 to 2021. The findings reveal that the war in Ukraine led to an increase in the level of higher education coverage among the young population, which contrasts with predicted decline in this indicator under the assumption of Ukraine’s stable development without the war, as indicated by the synthetic control model.

The significant gaps observed in the trajectories of tertiary education development in Ukraine from 2014 to 2021 can be attributed to several factors, including the intensification of reforms aimed at integrating higher education institutions into the European educational space, the growing demand for higher education despite the ongoing war, and Ukrainian economy increasing need for highly qualified specialists capable of contributing to high-tech military production. Additionally, it can be inferred that the onset of the war created conditions that led to an increased demand for higher education essential for the defence industry and technological advancement of the country. The results indicate that tertiary education could play a key role in Ukraine’s post-war recovery following the full-scale invasion in February 2022. Its capacity to swiftly adapt to unfavourable geopolitical conditions, develop a highly skilled workforce, and enhance labour productivity positions it as a vital component in the nation’s rebuilding process.

It is established that, in the absence of the war, the expected decline in interest in tertiary education in Ukraine would likely have been accompanied by a downward trend in the coverage of young people with higher education. This decline could have been attributed to Ukraine’ resource-based model of economic development, which trends to reduce demand for higher education, as well as the slower or stagnant reforms in tertiary education aimed at improving its quality and integration it into the European higher education area. Further analysis, based on empirical data, reveals a consistent upward trend in tertiary education enrolment in Ukraine between 2014 and 2021, accompanied by a slight reduction in gender disparity with a growing proportion of male students enrolling at the bachelor’s, master’s and PhD levels. This trend may be interpreted as a strategy for securing their future in the face of the unpredictable conditions resulting from the ongoing war in Ukraine.

Given the results, Ukraine’s educational policy initiatives should focus on further developing tertiary education, with an emphasis on maintaining its flexibility amidst the ongoing war, expanding access to international programmes and resources, and preserving and building upon the positive changes resulting from integration into the European higher education area. The trends identified through the SCM provide a foundation for a more in-depth analysis of the potential of tertiary education to address the challenges posed by the ongoing war.

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